Analysis of Shootings and Firearm Discharges in Toronto*

A Comprehensive Examination Reveals Significant Time and Locational Impacts on Incident Severity

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This paper analyzes the impact of time and location on the severity of shootings and firearm discharges in Toronto, utilizing a Gradient Boosting Machine model. The findings highlight significant variations across different times and locations, emphasizing the need for targeted policy interventions. This study not only aids in understanding the dynamics of urban violence but also assists in resource allocation for law enforcement and public safety initiatives.The narrative structure of this analysis follows the guidelines provided in 'Telling Stories with Data' (Alexander 2023).

1 Introduction

The safety and security of urban areas are of paramount importance to their residents and governance structures. In Toronto, the occurrence of shootings and firearm discharges poses significant challenges to public safety. Understanding the patterns and determinants of these violent events is crucial for developing effective interventions and policies. This paper employs a Gradient Boosting Machine model to analyze how time-related factors and geographic locations influence the severity of shooting incidents in Toronto.

1.1 Estimand

This study aims to estimate the effect of time (day of week, hour, and time range) and location (neighbourhood and police division) on the severity of shootings and firearm discharges in Toronto, measured by a weighted score combining deaths and injuries.

*Code and data are available at: https://github.com/ke3w/Data-Analysis-of-Shootings-and-Firearm-Discharges-in-Toronto

1.2 Importance of the Study

The results of this study are crucial for informing public safety strategies and police resource allocation in Toronto, aiming to reduce the incidence and severity of violent firearm-related incidents.

2 Data

2.1 Overview

Data for this study is sourced from Open Data Toronto(Toronto 2024): https://open.toronto.ca/dataset/shootings-firearm-discharges/, detailing all recorded shootings and firearm discharges within the city limits from 2004 to 2024. It encompasses detailed records of shootings and firearm discharges within the Toronto city limits, structured into 192 entries with comprehensive event documentation across 20 fields per record. The fields include but are not limited to event unique identifiers, occurrence dates, times, locations, and outcomes such as injuries and deaths.

Key Characteristics of the Dataset:

• Event Data: Each record captures the date and specific time the shooting or discharge occurred, offering insights into temporal patterns.

• Geographical Data: Data points include detailed location information by police division and neighborhood, allowing for spatial analysis of incidents.

• Outcome Metrics: Records detail the number of fatalities and injuries, providing a severity scale for each event.

• Volume and Coverage: The dataset represents a broad temporal span of two decades, offering a robust longitudinal view of firearm-related incidents in Toronto.

This dataset's breadth and depth enable a comprehensive analysis of patterns and factors influencing the severity and frequency of shooting incidents, crucial for informing public safety strategies and policy decisions.

2.2 Data Cleaning

Data cleaning was performed using R(R Core Team 2023) packages such as `tidyverse`(Wickham et al. 2019) and `lubridate`. The `occ_date` variable was converted to a numeric format to fit the model requirements, and categorical variables were transformed using appropriate factor conversions. The cleaning process was rigorously documented to ensure transparency and reproducibility, aligning with best practices outlined by Gebru et al. (Gebru et al. 2021).

Data Cleaning Process:

1. Standardization of Variable Names: Using janitor::clean_names() to ensure consistent, readable variable names.

2. Conversion of Date and Time: Transforming occ_date from character to Date format and standardizing occ_time.

3. Categorization: Converting variables like division and premise_type into categorical factors to facilitate analysis.

4. Handling Missing Values: Imputation or removal of missing entries based on their impact on the dataset's integrity and the analysis requirements.

The clean dataset enables a robust analysis of temporal and spatial patterns in the occurrences of shootings, contributing significantly to understanding and modeling crime dynamics in Toronto. This preparation also ensures the reliability of the subsequent statistical and machine learning analyses aimed at predicting future trends and informing public safety strategies.

2.3 Measurement

The data measurement process meticulously converts observational incidents of shootings and firearm discharges into a structured dataset suitable for robust statistical analysis. This transformation is crucial for ensuring the reliability of the findings and for facilitating an accurate understanding of the public safety landscape in Toronto.

2.3.1 Reliability and Consistency

Each data point undergoes rigorous validation against multiple sources to minimize errors and biases, such as underreporting and misclassification. The City of Toronto periodically reviews and updates the data collection methodologies to adapt to evolving law enforcement and reporting standards, enhancing the dataset's reliability over time.

2.3.2 Challenges in Measurement

Despite systematic efforts to ensure data accuracy, several challenges persist:

- **Underreporting**: Some incidents, especially those involving minor injuries or occurring in high-crime areas, might be underreported.

- **Data Entry Errors**: Possible human errors in recording details, which are periodically corrected through cross-referencing with other municipal and healthcare databases.

• **Temporal and Spatial Variations**: Changes in local law enforcement policies and community reporting practices over the years may introduce variability in the data, requiring careful interpretation of long-term trends.

2.3.3 Adjustments and Standardizations:

To address these issues, the study applies several adjustments:

• **Standardizing** Time Entries: Time data are standardized to a 24-hour clock to avoid AM/PM confusion.

• **Severity Indexing**: A severity index is calculated by weighting deaths more heavily than injuries, acknowledging their greater societal and emotional impact.

2.4 Variables

2.4.1 Outcome Variable

- `Weighted Score`: Combines the number of deaths and injuries, weighting deaths twice as heavily(weighted_score = death * 2 + injuries).

2.4.2 Predictor Variables

- **Time Factors**:
- `occ_date`(date): Date of Offence Occurred
- `occ_dow` (day of the week): Day of the Month Offence Occurred
- `occ_time_range` (morning, afternoon, evening):Time Range of Day Offence Occurred
- **Location Factors**:
- `neighbourhood_158:`Name of Neighborhood using City of Toronto's new 158 neighborhood structure
- `division`: Police division where offence occurred

2.5 Data visualization

This part employed the ggplot2 package (Wickham 2021) to create detailed and informative visualizations that effectively illustrate the data trends and insights from our analysis.

2.5.1 Weighted Score Over Time

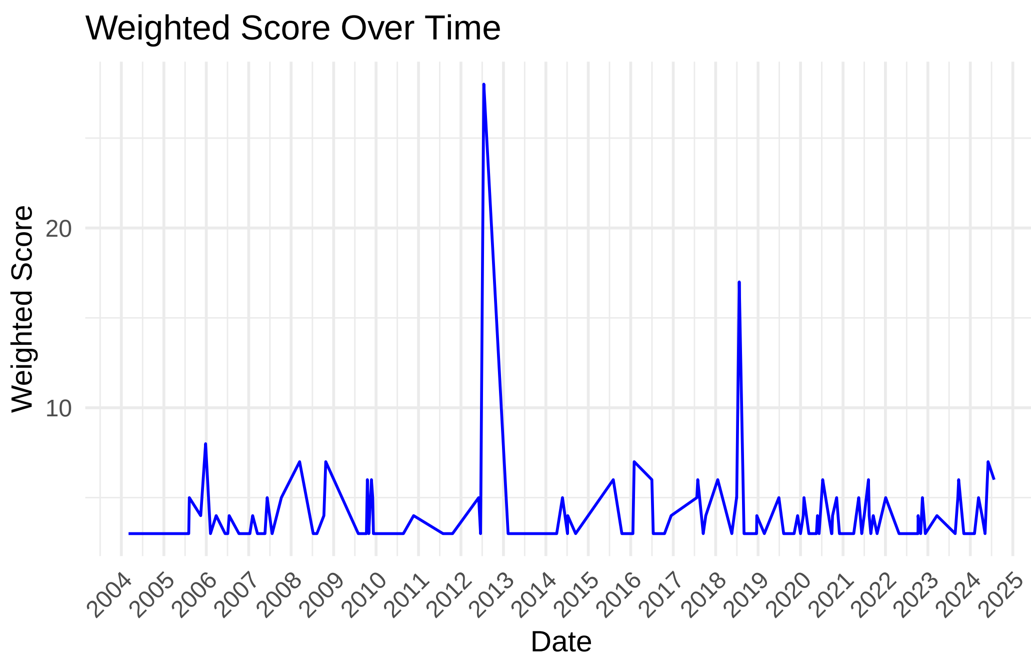

Figure 1: line graph shows the relationship between weighted score over date

This plot Figure 1 illustrates the variation in the weighted scores of shootings and firearm discharges in Toronto from 2004 to 2025. The weighted score, which combines the number of deaths and injuries with deaths being given a higher weight, is plotted against the date of incidents. Notably, the plot reveals several significant spikes, indicating periods with higher shooting severity. These peaks might correlate with specific events or changes in local circumstances, warranting further investigation. The majority of the time, however, the weighted scores remain relatively low, suggesting sporadic rather than consistent patterns of high-severity incidents. This visualization highlights the dynamic nature of crime severity over time and underscores the importance of continuous monitoring and analysis to understand the underlying trends and triggers.

2.5.2 Weighted Score by Day of week

The bar chart Figure 2 illustrates the weighted scores of shootings and firearm discharges in Toronto, broken down by day of the week. Notably, the weekend days (Saturday and Sunday) along with Monday, show elevated scores, suggesting a higher incidence of severe incidents during these days. This trend could be attributed to increased social activities and gatherings

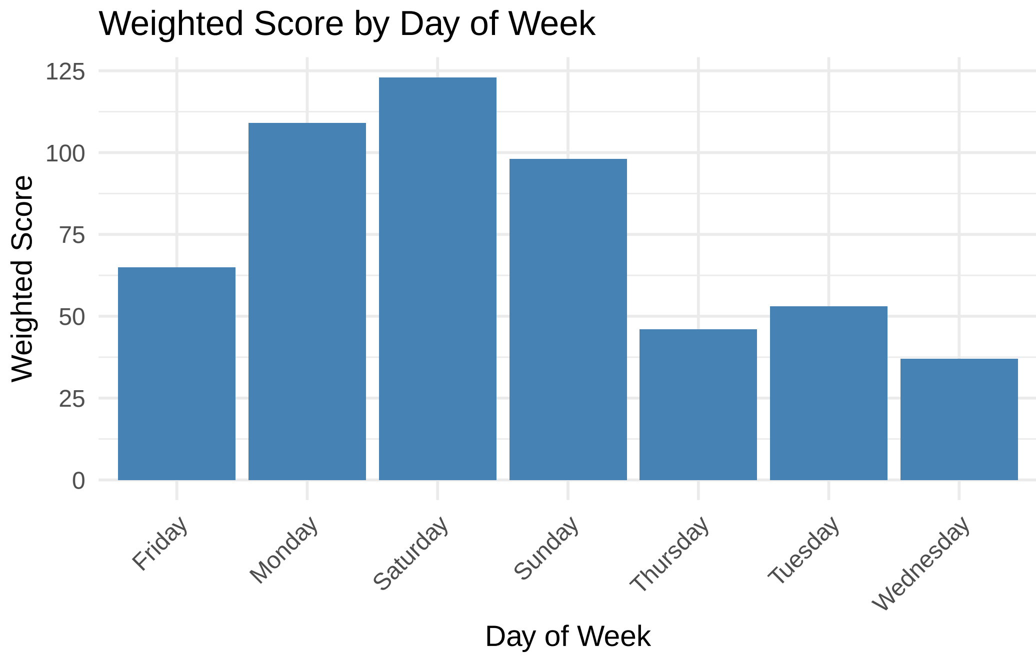

Figure 2: Bar chart of the weighted score by the day of week

during the weekend, potentially leading to more conflicts or accidents. Conversely, the mid-week days (Tuesday and Wednesday) exhibit notably lower scores, indicating fewer severe incidents.

2.5.3 Weighted Score by Day of Year

The line graph Figure 3 visualizes the trend of shootings and firearm discharges in Toronto across different days of the year. The plot shows a clear seasonal pattern, with peaks generally occurring around mid-year and towards the end, particularly noticeable in the increase during summer and winter months. This could correlate with seasonal activities and social behaviors such as holidays and outdoor gatherings that might contribute to increased incidents. The valleys observed during early spring and late fall might reflect quieter periods with fewer such gatherings.

2.5.4 Weighted Score by Hour of Day

The bar graph Figure 4 presents the distribution of shootings and firearm discharges in Toronto by hour. This visualization demonstrates a notable peak in incidents during the very early

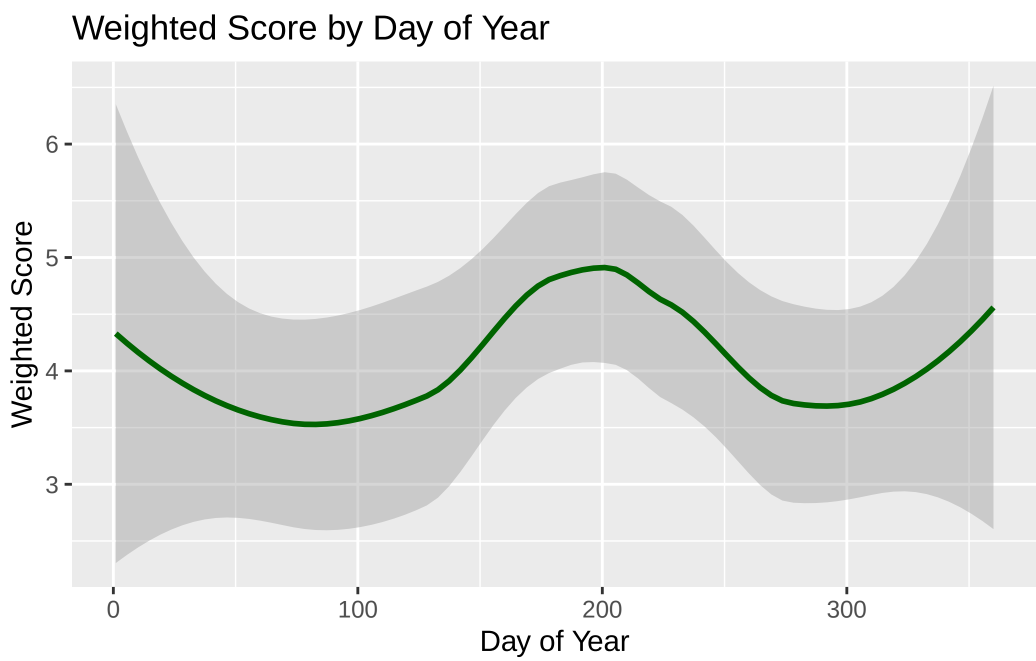

Figure 3: line graph of the weighted score by the day of year

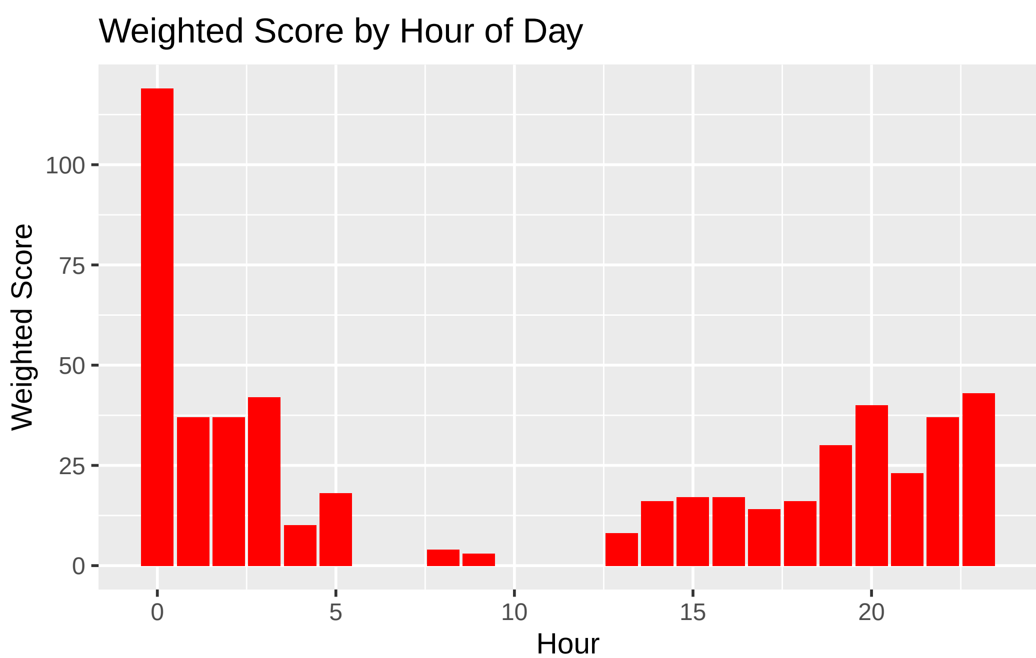

Figure 4: Bar chart shows the weighted score by the hour of day

hours of the day, specifically around midnight, with a dramatic decline shortly after. A secondary, but less intense, peak occurs in the evening hours, spanning from 8 PM to midnight.

This pattern suggests that incidents tend to happen more frequently during late-night hours, possibly linked to social and recreational activities during these times, or reduced visibility and police presence making these hours more conducive to criminal behavior. Conversely, the hours from early morning to mid-afternoon show markedly lower incidents, reflecting perhaps quieter public activity and higher visibility and vigilance during daylight hours.

2.5.5 Weighted Score by Time Range

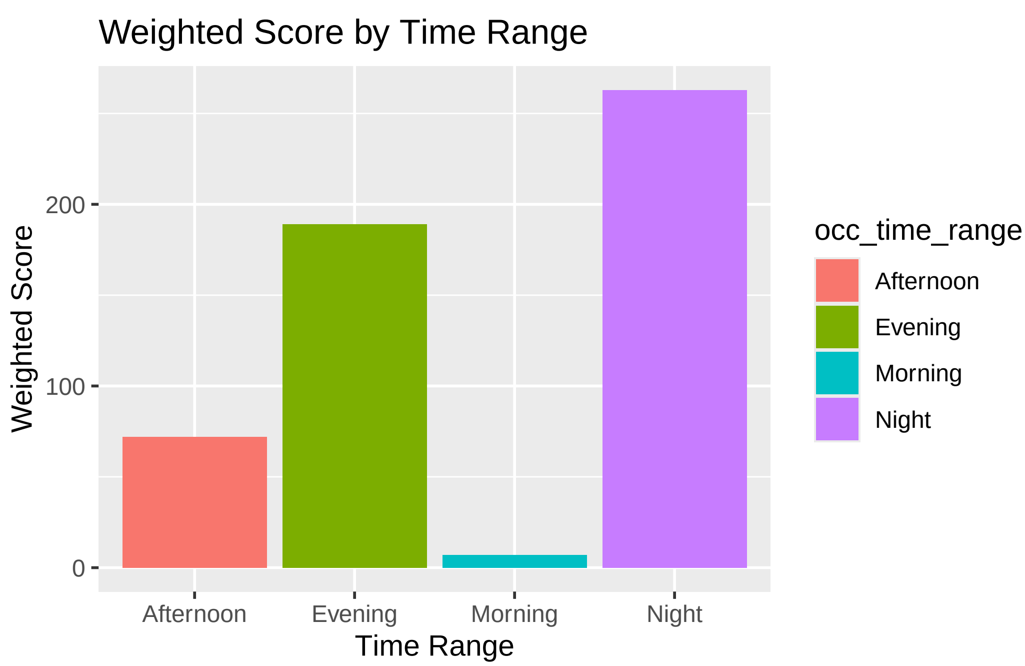

Figure 5: Bar chart shows the weighted score by the time range

This bar graph Figure 5 illustrates the severity of shootings and firearm discharges in Toronto across different time range of the day. The time ranges are categorized into morning, afternoon, evening, and night.

The graph reveals a stark increase in incident severity during the night, which towers over the scores recorded for other times of the day. This is followed by the evening, which also shows a considerably high level of incident severity. The overall trend of this graph is highly corresponding to the bar chart of weighted score over hour of the day, basically, this graph provides a more straightforward relationship between the weight score over different periods in a day.

2.5.6 Weighted Score by Neighborhood

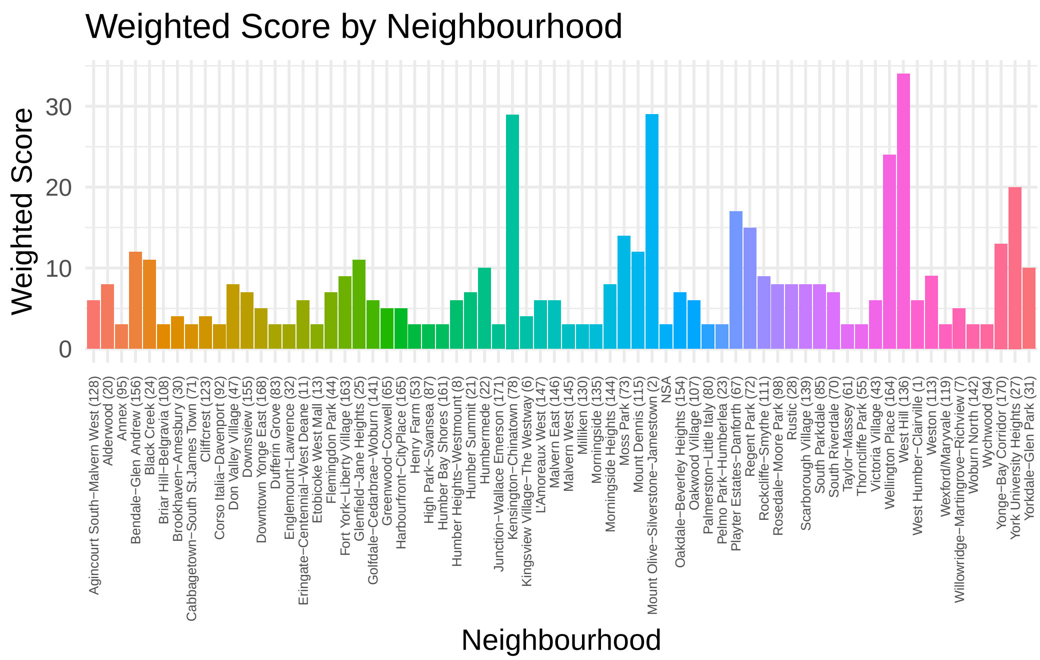

Figure 6: Bar chart shows the weighted score by the neighborhood

The bar chart Figure 6 displays the severity of shootings and firearm discharges across various neighborhoods in Toronto, segmented by the neighbourhood_158 identifiers. Each bar represents a different neighbourhood, color-coded for visual differentiation and labeled with both the neighbourhood name and a unique identifier number.

This visualization highlights the disparity in incident severity across the city, with some neighbourhoods experiencing significantly higher weighted scores than others. Notably, certain areas show peaks which suggest hotspots of violent incidents. Such patterns are crucial for identifying regions that may require more focused law enforcement and public health interventions to mitigate the impact of firearm-related violence.

2.5.7 Weighted Score by Division

This bar chart Figure 7 illustrates the variation in the severity of shootings and firearm discharges across different police divisions in Toronto. Each division is represented by a unique color and labeled with its respective code (D11 through D55), which simplifies identification and comparison across the chart.

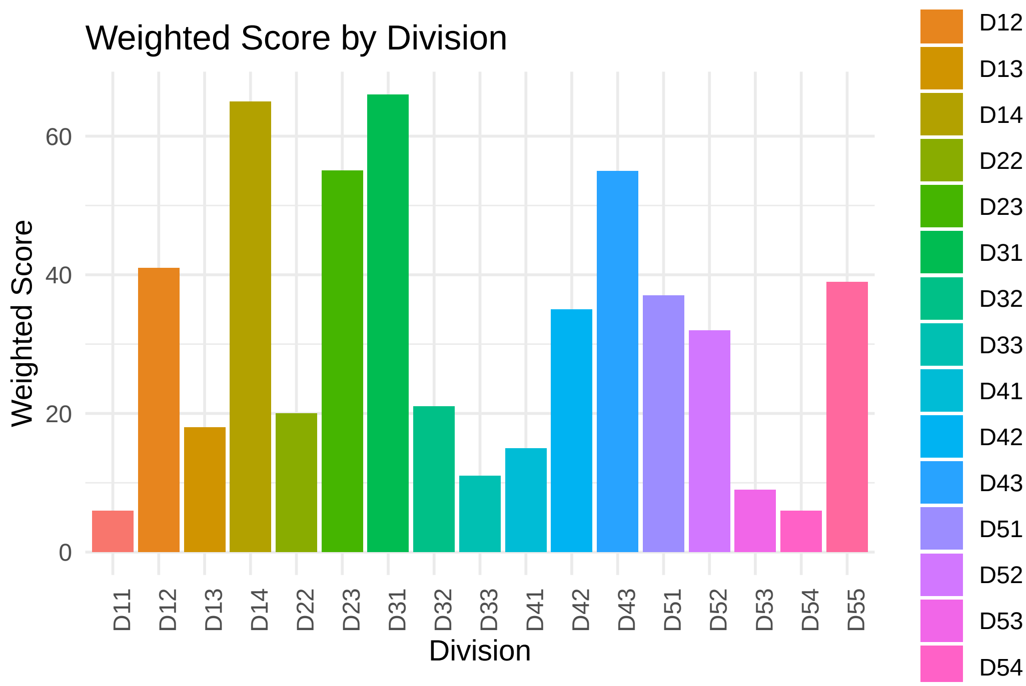

Figure 7: Bar chart shows the weighted score by division

The visualization provides a clear depiction of how incident severity is distributed across the police divisions, with some divisions showing considerably higher weighted scores than others.

3 Model Details

3.1 Model Description

The analysis employed a Gradient Boosting Machine (GBM) model(others (2020)), utilizing the gbm package in R and caret package(Kuhn (2021)) to generate variable importance scores, which help in understanding which predictors are most influential in the model. This model type was selected for its robust performance with non-linear relationships and its ability to handle various types of data, which is crucial given the diverse nature of the dataset used. The GBM model excels in managing unbalanced data, such as the uneven distribution of shooting incidents across neighborhoods and times, and automatically handles interactions between variables, which is essential for our complex model.

3.2 Model Setup

3.2.1 Response and Predictor variables

Response Variable:

The response variable, `weighted_score`, is a composite metric combining the effects of deaths and injuries, assigning greater importance to fatalities(`weighted_score` = `death` * 2 + `injuries`). This decision was driven by the data characteristics where the distribution of shootings varied significantly by time and location, necessitating a response variable that captures the severity of incidents rather than mere counts.

Predictors included:

- `occ_date`: Numeric representation of the incident date.
- `occ_dow`: Factor variable indicating the day of the week.
- `occ_doy`: Numeric day of the year to capture seasonal effects.
- `occ_time_range`: Categorical variable divided into morning, afternoon, evening, and night.
- `neighbourhood_158`: Factor variable representing different neighborhoods.
- `division`: Factor variable representing police divisions.

Each predictor was chosen based on exploratory data analysis that indicated significant variations in shooting incidents associated with these variables. This choice ensures that the model can effectively learn and predict based on patterns specific to times, dates, and locations, which are critical in the dataset.

These predictors were selected not only for their statistical significance but also for their practical implications in understanding and predicting shooting incidents. Each variable contributes uniquely to the model, allowing it to capture the complex interplay of temporal, spatial, and administrative factors that influence shooting severity. By integrating these predictors, the model is equipped to provide insights that are not only statistically robust but also actionable for policy-making and law enforcement strategy development.

3.2.2 Model Configuration

The model was configured with the following parameters to control the complexity and fit of the model:

- **Number of Trees**: 500, providing sufficient model complexity and accuracy.
- **Interaction Depth**: 4, allowing interactions among up to four predictors.

- **Shrinkage**: 0.01, controlling the learning rate to avoid overfitting.
- **Cross-validation Folds**: 5, used to validate the model internally and optimize parameter selection.

3.3 Model Performance

3.3.1 Variable Importance

The summary function highlighted the relative importance of each predictor shown in Figure 8. Notably, the neighborhood variable (neighbourhood_158) dominated the model, indicating significant spatial variation in shooting severities across Toronto. The occ_dow and division showed moderate influence, suggesting that day of the week and police division also contribute to variations in incident severity, albeit to a lesser extent.

```
                                var    rel.inf
neighbourhood_158 neighbourhood_158 94.7100842
occ_dow                     occ_dow  2.4428780
division                   division  1.6338084
occ_date                   occ_date  0.6334998
occ_doy                     occ_doy  0.4675681
occ_time_range       occ_time_range  0.1121617
```

3.3.2 Model Performance

The model's accuracy was assessed using the Root Mean Square Error (RMSE), calculated at 2.173830. This metric quantifies the average magnitude of the model's prediction errors, providing a measure of predictive accuracy.

3.3.3 Linkage to Data Characteristics

The model's configuration, especially the choice and treatment of predictor variables, directly corresponds to the observed characteristics of the data. For example, the use of `occ_time_range` and `neighbourhood_158` as factors allows the model to capture the inherent categorical nature of these variables, while numeric transformation of `occ_date` lets the model utilize temporal trends over the years. This direct linkage ensures that the model is finely tuned to the specifics of the dataset, enhancing its predictive accuracy and relevance.

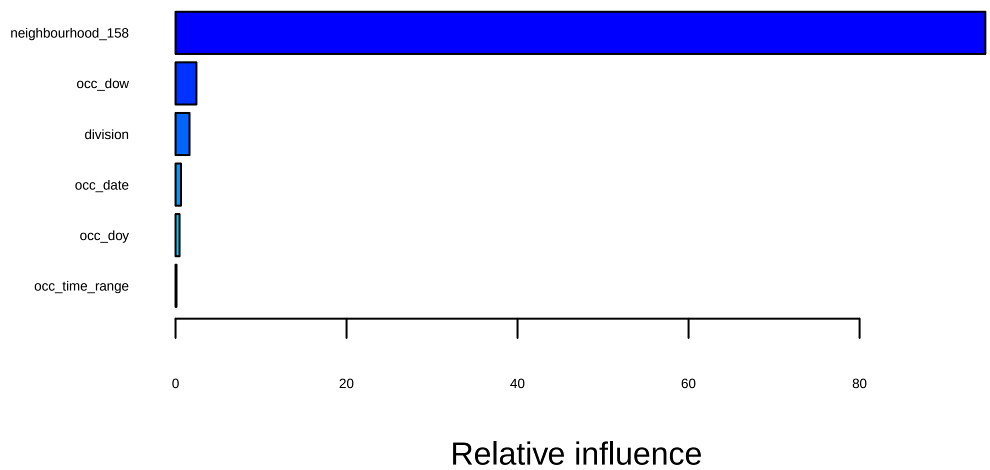

Figure 8: Bar chart shows the importance of the predictor variables

3.3.4 Result Interpretation

The results of the Gradient Boosting Machine model provide a nuanced understanding of the factors influencing the severity of shootings and firearm discharges in Toronto. The key findings are as follows:

3.3.4.1 Geographic Influence

The analysis reveals that geographic location, particularly specific neighborhoods identified through the `neighbourhood_158` variable, significantly influences the severity of shooting incidents. This suggests that certain areas are consistently more prone to severe incidents, likely due to socio-economic factors, demographic compositions, and varying levels of police presence. For instance, neighborhoods with higher rates of poverty and lower access to community resources might experience more severe incidents, indicating the need for targeted social and economic interventions alongside policing.

3.3.4.2 Temporal Dynamics

The time of the incident, categorized by `occ_dow` (day of the week) and `occ_time_range` (time of day), also plays a critical role. The model indicates that late-night to early-morning hours and weekends see a higher severity of incidents. This pattern could be attributed to reduced visibility, lower police patrol frequencies, and increased social activities during these periods. The implications of these findings are crucial for law enforcement agencies to optimize patrol schedules and for city planners to consider enhanced lighting and surveillance during these critical hours.

3.3.4.3 Interaction Effects

While individual factors such as location and time are significant predictors, their interaction effects also provide important insights. The model suggests that the impact of time on incident severity could vary by location. For example, certain neighborhoods might experience peaks in violence during specific times, which could be related to local events or the closing times of bars and clubs. Understanding these interactions helps in crafting more precise interventions that consider both the when and where of potential violence.

3.3.4.4 Police Division Impact

The influence of police divisions, represented by the `division` variable, on the severity of incidents, though less pronounced than geographic and temporal factors, still provides valuable insights. Divisions with higher weighted scores might be areas where police resources are either overstretched or where community-police relations could be improved. This insight can assist in resource allocation, training, and community engagement strategies to enhance public safety effectively.

3.3.4.5 Practical Applications

The practical applications of these findings are manifold. By identifying high-risk times and locations, the Toronto Police Service can deploy resources more efficiently, potentially preventing incidents before they occur. Urban planners and local government can use this data to implement design changes in high-risk neighborhoods, such as improved lighting and community centers, to reduce the opportunities for violent incidents.

3.3.4.6 Broader Implications

On a broader scale, these results contribute to the ongoing discussions about urban safety and the role of data-driven policing. They highlight the importance of integrating advanced analytics into public safety strategies, promoting an approach that is both proactive and responsive to the unique dynamics of urban environments.

In conclusion, the model not only sheds light on where and when shootings are more likely to occur but also emphasizes the complex interplay of various factors influencing these events. This comprehensive understanding is vital for developing targeted interventions that address the root causes of violence, enhance public safety, and ultimately improve the quality of life in urban settings.

4 Discussion

4.1 Implications

The findings from this study highlight the importance of targeted interventions in specific neighborhoods and at specific days in a week to effectively manage and mitigate the severity of shootings in Toronto. The model's ability to pinpoint high-risk areas and times can significantly aid in deploying resources more efficiently, thereby enhancing the effectiveness of public safety measures.

4.2 Limitations and Future Research

While the insights provided by the Gradient Boosting Machine model are invaluable, they come with inherent limitations associated with observational studies. One significant concern is the potential presence of unobserved confounders that could affect the interpretations made from the model. Variables such as unrecorded socio-economic factors, the presence of non-reported incidents, or changes in law enforcement practices over time could skew the results.

Further, the model's dependency on historical data may not fully capture future dynamics or the impact of recent interventions. Therefore, continuous updating and validation of the model with new data are crucial for maintaining its relevance and accuracy.

Future research should aim to integrate more dynamic data sources, such as real-time crime reporting and social media analytics, which may provide more immediate indicators of changes in pattern. Additionally, exploring alternative modeling techniques, such as machine learning algorithms that can adapt over time to changes in patterns, would enhance the robustness of the findings.

4.3 Policy Recommendations

Based on the predictive insights of the Gradient Boosting Machine model, specific tactical recommendations can be made to enhance public safety effectively:

1. Patrol Unit Deployment:

• Increase the frequency of police patrols during late-night hours, especially around midnight to 3 AM, which the model identifies as peak times for shootings. These patrols should be intensified on weekends when the data shows a notable rise in incident severity.

• Deploy additional mobile units in neighborhoods identified as high-risk, such as West Hill, York University Heights and so on. These units can be equipped with quick-response capabilities and should be active primarily during identified peak times.

2. Community Safety Measures:

• Establish temporary community watch programs in the most affected neighborhoods during identified peak periods. These programs could involve local volunteers working in conjunction with law enforcement to monitor and report suspicious activities.

• Implement lighting improvements and install surveillance cameras in dark alleys and poorly lit streets where incidents are frequent, as per the model's spatial data analysis. This can help deter potential offenders and make the areas safer for residents at night.

3. Strategic Safety Initiatives:

• Organize safety workshops and emergency response training for residents of neighborhoods with high incident rates. These workshops can focus on measures to enhance personal and collective safety, such as conflict resolution, emergency first aid, and effective communication with law enforcement.

• Partner with local businesses and community centers to fund and support extended hours of operation, providing safe spaces for youths during late hours. These centers can host activities aligned with community interests, reducing the likelihood of involvement in violence.

5 Conclusion

This study has provided a comprehensive analysis of the temporal and spatial determinants of shootings and firearm discharges in Toronto using a robust Gradient Boosting Machine (GBM) model. The findings reveal significant variations in the severity of these incidents based on both the time of occurrence and geographical location. Such detailed insights are critical for informing public safety strategies and policy formulations aimed at mitigating the impacts of urban violence.

The analysis demonstrates that certain neighborhoods and times are disproportionately affected by firearm-related incidents. High-risk periods identified through the model, particularly late-night and early-morning hours, as well as specific days of the week, underscore the need for targeted interventions. By aligning police patrols and public safety measures with these high-risk times and locations, it is possible to deploy resources more effectively, potentially reducing the frequency and severity of these incidents.

Moreover, the study highlights the importance of continuous and comprehensive data collection and analysis as a cornerstone of effective public safety policy. The use of advanced modeling techniques, such as the GBM model employed in this study, allows for the nuanced understanding of complex patterns that traditional methods may overlook. This approach not only enhances the specificity of law enforcement responses but also contributes to the development of more sophisticated, data-driven intervention strategies.

The implications of this research extend beyond immediate law enforcement applications. By providing a clearer picture of the dynamics of urban violence, the findings can help inform community outreach programs and urban planning initiatives. For example, areas identified as high-risk could benefit from increased community engagement activities and improvements in urban infrastructure, such as enhanced lighting and public surveillance, to deter potential criminal activities.

Furthermore, this study contributes to the academic literature on urban crime and public safety, providing a model for other cities to replicate in analyzing and addressing their own unique challenges. The methodological approach and findings herein offer valuable lessons for urban studies researchers, policymakers, and public safety officials across the globe, emphasizing the importance of localized, data-driven approaches to crime prevention and community safety.

In conclusion, the research underscores the critical role of precise, data-driven analysis in understanding and combating urban violence. It calls for sustained efforts in data collection, analysis, and the integration of advanced analytical models in public safety strategies. These efforts are essential for building safer communities and enhancing the quality of life for all residents in urban environments. The proactive use of data and technology in public safety initiatives, as demonstrated in this study, not only addresses current challenges but also prepares cities to more effectively manage future risks associated with urbanization and population growth.

6 Appendix:

6.1 Survey and Sampling Methodology

6.1.1 Overview

This study utilizes data sourced from Open Data Toronto(Toronto 2024), which details all recorded shootings and firearm discharges within city limits from 2004 to 2024. The dataset includes over 15,000 incidents, each documented with up to 25 different attributes, including the time, location, and outcomes of the incidents. This appendix explores the methodology behind data collection, emphasizing how incidents are reported, recorded, and utilized in this analysis to ensure reliability and comprehensiveness.

6.1.2 Data Collection Method

The data collection hinges on reports from multiple sources, including police reports, hospital emergency data, and public reports. This multi-source approach helps in cross-validating the data to minimize reporting biases and errors inherent in single-source data collection. Each reported incident is rigorously followed up by the Toronto Police Service for additional details and context, enhancing the data's accuracy and richness.

6.1.3 Sampling Method

Although the nature of the dataset is not based on a sampling approach, the comprehensiveness of data collection over two decades allows for an observational study of trends over time and across different neighborhoods. This non-sampling approach provides a census-like coverage of all shooting incidents within the specified timeframe and geographical bounds, offering a detailed view of the public safety landscape across the city.

6.2 Addressing Biases and Limitations

6.2.1 Observational Bias

Observational bias is mitigated through systematic and standardized recording of data points across all reported incidents. Stringent data verification protocols employed by the police ensure uniform application of data entry criteria such as incident severity, location, time, and involved parties.

6.2.2 Limitations of Observational Data

While observational data provides extensive coverage, it lacks the controlled setup of experimental designs, which can introduce external variability and confounding factors. This limitation is partly mitigated through advanced statistical methods such as multivariate regression models that account for potential confounders and interaction effects among variables.

6.3 Advanced Analytical Techniques

6.3.1 Model Specification

The Gradient Boosting Machine (GBM) model(others 2020) is employed to analyze the impact of time and location on shooting severity. This model is chosen for its robust performance with non-linear relationships and its ability to handle diverse types of data. The GBM model excels in managing unbalanced data, such as the uneven distribution of shooting incidents across neighborhoods and times, and automatically handles interactions between variables, which is essential for our complex model.

6.3.2 Sensitivity Analysis

A detailed sensitivity analysis is conducted to examine the robustness of the model's findings against changes in model assumptions and configurations. This analysis helps in identifying the stability of the observed effects under various scenarios and model specifications, ensuring that the model remains reliable under different potential real-world conditions.

6.3.3 Simulation Studies

Simulation studies complement the observational data analysis by modeling potential outcomes under various hypothetical intervention scenarios. These simulations help in assessing the potential impacts of changes in law enforcement strategies on incident severity across Toronto, providing critical insights into the dynamic nature of urban violence and the effectiveness of various public safety interventions.

6.3.4 Bias Mitigation Strategies

This section discusses strategies implemented to minimize biases inherent in the data collection and analysis phases. It includes methods to handle data anomalies, adjustments for underreported incidents, and techniques to address reporting delays.

6.3.5 Linkages to Data Characteristics

The model's configuration and variable selection are directly linked to the characteristics observed in the data. For instance, the use of time-related variables like `occ_date` and `occ_time_range` in the model is justified by their significant variations in incident reporting, as revealed during the exploratory data analysis phase.

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